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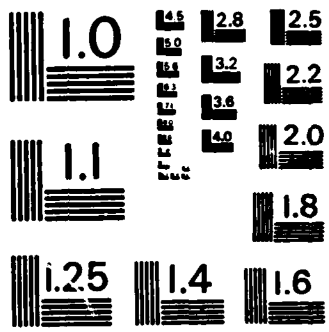

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CATEGORY ANALYSIS OF THE MARINE CORPS COMBAT READINESS EVALUATION SYSTEM (MCCRES)

by

S. Zacks, W. H. Marlow and Zeev Barzily

Serial T-450
15 October 1981

The George Washington University
School of Engineering and Applied Science
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CATEGORY ANALYSIS OF THE MARINE CORPS COMBAT READINESS EVALUATION SYSTEM (MCCRES)

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1. Introduction

The Marine Corps Combat Readiness Evaluation System (MCCRES) and various analyses have been discussed recently in a series of papers by Barzily, Catalogne and Marlow [2], Zacks and Marlow [7] and Barzily, Marlow, and Zacks [8]. In the present paper we conduct statistical analysis of MCCRES from the point of view of the ten categories introduced by Barzily [1]. As in the previous work we restrict our present attention to Volume II of MCCRES, which deals with infantry battalions and contains 800 different requirements. The category approach of Barzily classifies all requirements into the following ten categories.

1. REPORTING to higher levels of command
2. PREPARING for operation
3. COMMUNICATING
4. PERFORMING as Marines
5. DELIVERING supporting fire
6. PLANNING of operations
7. CONFORMING to doctrine

8. EXECUTING operations

9. PROVIDING combat service support

10. SUPERVISING required actions of individual Marines

In a given evaluation an infantry battalion is evaluated on a subset of the 800 requirements. That is, due to time, budget, and other constraints, not all 800 requirements are applicable. The battalion is given a score of "Yes" in case a requirement is fulfilled satisfactorily, and a score of "No" otherwise. The basic assumption in our category approach is that the probability of "Yes" for a given unit is the same for all the applicable requirements of the same category (see Appendix 1). These probabilities may change from one category to another. The vector of the ten probabilities, corresponding to the ten categories, is a parametric vector which characterizes the unit at that particular evaluation. Different units usually have different characterizing parametric vectors and the same unit may have different characterizing parametric vectors in different evaluations. In addition to the parametric vector of "Yes" probabilities, there are several other interesting statistical features of the data. The proportion of "Yes's" among the applicable requirements of different categories in the same evaluation are not independent. It is interesting to study the correlation structure between these categories. In the present study we present statistical models and develop procedures designed to estimate interesting model parameters. We base the analysis on the results of $N = 27$ evaluations. The statistical methods developed here have a wide range of possible applications for the analysis of categorical data in which a different number of independent Bernoulli trials are performed in each category, but the proportions of successes in different categories are dependent variables.

2. The Structure of the Data and the Statistical Model

Let N designate the number of evaluations, $N = 27$, and k designate the number of categories, $k = 10$. Let X_{ij}, $i=1,\ldots,N$, $j=1,\ldots,k$ designate the number of "Yes's" among the applicable requirements of the

j-th category in the i-th evaluation. Let M_{ij} , $i=1,\dots,N$, $j=1,\dots,k$ designate the corresponding number of applicable requirements. In Table 2.1 we present the values of X_{ij} and M_{ij} which have been compiled from MCCRES data files. All the analyses in the present paper are based on the data in this table.

Let $\underset{\sim}{X}_i$ $(i=1,\dots,N)$ designate the vector of k X - values corresponding to evaluation i , and $\underset{\sim}{M}_i$ the vectors of corresponding M - values. The fundamental assumptions of the statistical model are:

A.1 $\underset{\sim}{X}_1$, $\underset{\sim}{X}_2,\dots,\underset{\sim}{X}_N$ are independent random vectors;

A.2 The marginal distribution of X_{ij} is binomial, $B(M_{ij}, \theta_{ij})$, for all $i=1,\dots,N$, and $j=1,\dots,k$. θ_{ij} designates the probability of "Yes" for all the requirements in evaluation i and category j .

In Appendix 1 we test a null hypothesis which is based on assumption A.2. This hypothesis is accepted by the data in such a way to provide substantial empirical verification.

The multivariate distributions of $\underset{\sim}{X}_i$, $i=1,\dots,N$, are specified indirectly by considering first the following transformations. Let

$$Y_{ij} = 2 \sin^{-1}\left(\sqrt{\frac{X_{ij} + 1/2}{M_{ij} + 1}}\right), \quad \begin{array}{l} i=1,\dots,N \\ j=1,\dots,k \end{array} \tag{2.1}$$

These transformations are known as variance stabilizing transformations for binomial random variables (see Johnson and Kotz [3; p. 65], who suggest the transformation $Y = 2 \sin^{-1} \sqrt{\hat{\theta}}$, where $\hat{\theta} = (x + 3/8)/(M + 3/4)$. The asymptotic properties of (2.1) and of this one are the same).

Table 2.1

Total number of satisfied and applicable requirements by category and evaluation*

EVAL/CAT.	1	2	3	4	5	6	7	8	9	10
1	62	44	40	14	55	100	50	53	24	13
	67	54	40	23	69	110	63	73	32	17
2	79	70	42	18	67	133	65	97	31	17
	80	76	44	24	72	140	73	100	37	20
3	41	19	26	12	45	38	44	47	15	12
	42	26	28	21	56	45	53	54	16	14
4	60	33	25	20	53	68	49	68	18	16
	62	36	31	24	55	71	54	72	19	16
5	35	34	35	21	52	93	48	46	18	12
	52	44	37	24	54	99	54	67	21	14
6	52	29	20	23	57	60	59	62	18	18
	55	29	29	24	63	63	61	67	18	18
7	44	41	32	15	63	90	47	50	30	13
	47	46	34	21	64	93	51	55	31	17
8	29	18	28	12	48	40	34	65	7	9
	60	48	32	22	63	81	57	87	14	15
9	64	41	36	25	64	78	44	93	16	18
	71	48	37	26	64	90	57	104	18	18
10	64	48	35	19	60	99	45	67	25	17
	70	55	38	24	67	119	61	77	30	17
11	15	4	23	18	56	15	30	17	13	11
	15	4	23	18	56	15	31	17	13	12
12	12	5	14	16	35	10	16	12	8	7
	14	8	17	16	54	16	30	18	10	10
13	11	11	5	6	6	15	8	36	2	5
	11	11	6	9	6	16	10	37	2	5
14	54	31	23	17	57	55	49	62	16	13
	54	35	27	25	59	62	57	70	17	18
15	41	21	13	16	4	36	33	44	13	11
	42	23	17	23	4	36	35	47	13	16
16	49	35	29	13	59	73	59	63	18	12
	54	38	32	23	59	74	63	70	18	16
17	44	29	18	16	9	52	44	54	18	13
	47	30	21	23	9	52	45	55	19	13
18	69	40	35	26	62	76	66	87	22	14
	69	41	36	28	63	78	68	90	22	16
19	78	43	38	27	64	90	60	92	19	17
	79	51	38	27	65	98	71	108	20	17
20	48	26	25	13	58	49	38	56	16	17
	54	31	29	24	61	61	56	67	18	18
21	18	5	14	4	41	14	22	12	12	9
	24	11	21	17	56	22	36	28	14	15
22	71	35	29	21	52	85	45	85	24	19
	73	37	34	25	66	92	54	90	24	20
23	71	41	33	26	63	87	63	93	21	15
	73	41	36	28	64	88	68	97	23	16
24	47	30	28	22	55	61	52	49	13	16
	49	31	30	25	57	63	57	58	15	17
25	44	32	29	16	31	56	50	47	15	16
	48	34	32	25	61	64	58	58	16	18
26	34	29	24	21	52	48	32	42	15	14
	37	32	27	23	58	56	40	54	15	15
27	100	58	32	27	69	121	75	136	26	18
	101	58	38	29	71	122	78	138	28	19

*The upper number in each cell represents the total number of satisfied requirements; the lower number represents the total number of applicable requirements.

For large values of M_{ij} the random variables Y_{ij} are distributed approximately normally, with mean $\eta_{ij} = 2 \sin^{-1} \sqrt{\theta_{ij}}$ and variance $1/M_{ij}$. Let $\underset{\sim}{Y}_i = (Y_{i1}, \ldots, Y_{ik})'$ be the k-variate vector of the transformed X-values of the i-th evaluations. According to assumption A.1, $\underset{\sim}{Y}_1, \ldots, \underset{\sim}{Y}_N$ are independent random vectors. We introduce here a third assumption concerning the multivariate distribution of $\underset{\sim}{Y}_i$ $(i=1,\ldots,N)$.

A.3 The random vectors $\underset{\sim}{Y}_i$ have multivariate normal distributions with means $\underset{\sim}{\eta}_i = (\eta_{i1}, \ldots, \eta_{ik})'$ and covariance matrices $\Sigma_i = (\Sigma_{i.jj'})$,

where

$$\Sigma_{i.jj'} = \begin{cases} \dfrac{1}{M_{ij}} , & \text{if } j=j' \\ \rho_{jj'} \Big/ \sqrt{M_{ij} M_{ij'}} , & \text{if } j \neq j' . \end{cases} \tag{2.2}$$

$\rho_{jj'}$ is the correlation between Y_{ij} and $Y_{ij'}$.

It is assumed that the correlations $\rho_{jj'}$ are the same for all evaluations. In Appendix 2 we show that $\rho_{jj'}$ are asymptotically equivalent to the correlations between the proportions of Yes's, $\hat{\theta}_{ij} = X_{ij}/M_{ij}$.

3. The Bayesian Framework

The Bayesian model assumes that the characterizing parametric vectors $\underset{\sim}{\theta}_i$ of the different evaluations vary according to a (prior) distribution of all possible evaluations. This is a model of a superpopulation which makes it possible to relate the information obtained from all evaluations in a consistent manner. Following the model developed in the previous section, we present here the Bayesian model in terms of the distributions of $\underset{\sim}{Y}_i$ $(i=1,\ldots,N)$.

We assume that the mean vectors $\underset{\sim}{\eta}_i$ of the distributions of $Y_i (i=1,\ldots,N)$ have a prior normal distribution with mean vector $\underset{\sim}{\bar{\eta}}$ and diagonal covariance matrix (D). The overall distribution of Y_{ij}, where η_{ij} are treated as random variables, is called a <u>predictive</u> distribution. According to the above assumption, the predictive distribution of each $\underset{\sim}{Y}_i$ is normal with the same mean, $\underset{\sim}{\bar{\eta}}$, and covariance matrix $\ddagger_i + (D)$ (see Zacks [6; p. 296]). The predictive marginal distributions of the components Y_{ij} are normal with means $\bar{\eta}_j$ $(j=1,\ldots,k)$ and variances $\tau_{ij}^2 = \frac{1}{M_{ij}} + D_j^2$ $(i=1,\ldots,N\ ,\ j=1,\ldots,k)$. Since we assumed that the correlations $\rho_{jj'}$ are the same for all evaluations, we will treat the vectors $\underset{\sim}{\bar{\eta}}$, and the matrices (D) and $(R) = (\rho_{jj'}\ ;\ j,j' = 1,\ldots,k)$ as unknown but fixed parameters. We remark that the predictive marginal distributions of Y_{ij} resemble the distributions of the observations in Model II of Analysis of Variance (see Zacks [6; p. 79]), in which the components of variance are $1/M_{ij}$ (known) and D_j (unknown). We conclude this section by specifying the posterior distributions of η_{ij} given Y_{ij}. According to the Bayesian model, the posterior distribution of η_{ij} given Y_{ij} is normal with mean

$$E\ \{\eta_{ij} | Y_{ij}\} = (\bar{\eta}_j + D_j M_{ij} Y_{ij})/(1 + D_j M_{ij})\ , \tag{3.1}$$

and variance

$$V\ \{\eta_{ij} | Y_{ij}\} = D_j/(1 + M_{ij} D_j) \tag{3.2}$$

Notice that the Bayes estimator of η_{ij} for a squared-error loss is given by (3.1), with a Bayes risk given by (3.2). If $\bar{\eta}_j$ and D_j are unspecified, one can estimate them from the data, to obtain empirical Bayes estimators of the characterizing parameters (see Zacks [6; p. 321]).

4. Bayesian Confidence Inrervals for the Characterizing Parameters

Bayesian confidence intervals, at level $1-\alpha$, for specified parameters, are defined as the intervals in the parameter space whose posterior coverage probabilities, given the sample data, are at least $1-\alpha$. According to the model of Section 3, the posterior coverage probability of the intervals

$$\frac{\bar{\eta}_j + D_j M_{ij} Y_{ij}}{1 + I_j M_{ij}} \pm Z_{1-\alpha/2} \left[\frac{D_j}{1 + M_{ij} D_j}\right]^{1/2} \tag{4.1}$$

is $(1-\alpha)$, where Z_γ is the γ-th fractile of the standard normal distribution. We determine for each category empirical estimates of the prior parameters $\bar{\eta}_j$ and D_j and, by substituting these estimates in (4.1), we obtain empirical Bayes confidence intervals for η_{ij} $(i=1,\ldots,N)$. The substitution of estimates of $\bar{\eta}_i$ and D_j for the correct values will generally effect the coverage probabilities. The estimates described below are consistent, and we expect that, for large values of N , the actual coverage will be close to the nominal one. In order to provide conservative intervals, we have used in each category, the Bonferroni method of simultaneous confidence intervals, for all the $N = 27$ evaluations (see Miller [4]). For this purpose we replaced α in (4.1) by $\alpha' = \alpha/N$.

Applying the transformation

$$\theta = \sin^2(\eta/2) , \tag{4.2}$$

which is strictly increasing for $0 \leq \eta \leq \pi$, we can obtain from the η - confidence intervals θ - confidence intervals. These intervals, for the ten categories and twenty seven evaluations with $\alpha = .05$, are presented in Table 4.1.

Table 4.1

CONFIDENCE INTERVALS FOR CAT. C1-C5

	1		2		3		4		5	
EVAL	L	U	L	U	L	U	L	U	L	U
1	0.802	0.987	0.648	0.942	0.849	0.999	0.366	0.882	0.661	0.926
2	0.902	1.000	0.794	0.982	0.802	0.988	0.481	0.942	0.809	0.988
3	0.834	1.000	0.519	0.942	0.751	0.984	0.333	0.872	0.655	0.940
4	0.853	0.999	0.723	0.991	0.683	0.956	0.556	0.972	0.834	0.999
5	0.548	0.881	0.592	0.931	0.782	0.987	0.598	0.984	0.832	0.999
6	0.814	0.995	0.820	1.000	0.625	0.931	0.699	1.000	0.769	0.980
7	0.791	0.995	0.717	0.980	0.772	0.986	0.437	0.935	0.880	1.000
8	0.397	0.749	0.269	0.668	0.723	0.972	0.318	0.855	0.622	0.912
9	0.778	0.977	0.680	0.964	0.807	0.993	0.717	1.000	0.913	1.000
10	0.792	0.983	0.711	0.968	0.763	0.981	0.517	0.958	0.763	0.975
11	0.755	1.000	0.509	1.000	0.794	0.997	0.714	1.000	0.902	1.000
12	0.634	0.997	0.407	0.982	0.679	0.973	0.688	1.000	0.514	0.858
13	0.716	1.000	0.659	1.000	0.668	0.986	0.328	0.969	0.621	1.000
14	0.900	1.000	0.685	0.984	0.704	0.969	0.427	0.909	0.843	0.999
15	0.834	1.000	0.669	0.996	0.658	0.966	0.432	0.922	0.582	1.000
16	0.768	0.985	0.734	0.992	0.743	0.979	0.335	0.860	0.906	1.000
17	0.791	0.995	0.767	1.000	0.698	0.975	0.432	0.922	0.669	1.000
18	0.920	1.000	0.817	1.000	0.804	0.993	0.682	0.995	0.878	1.000
19	0.901	1.000	0.673	0.957	0.844	0.999	0.793	1.000	0.881	1.000
20	0.747	0.979	0.626	0.972	0.712	0.970	0.321	0.843	0.824	0.996
21	0.586	0.965	0.331	0.929	0.621	0.943	0.128	0.711	0.589	0.903
22	0.871	0.999	0.762	0.997	0.712	0.965	0.568	0.973	0.649	0.924
23	0.871	0.999	0.865	1.000	0.757	0.980	0.682	0.995	0.880	1.000
24	0.823	0.998	0.772	1.000	0.758	0.985	0.609	0.985	0.839	0.999
25	0.770	0.990	0.747	0.997	0.743	0.979	0.396	0.890	0.401	0.754
26	0.753	0.994	0.699	0.991	0.724	0.977	0.634	0.994	0.754	0.979
27	0.921	1.000	0.901	1.000	0.709	0.960	0.691	0.995	0.866	0.999

CONFIDENCE INTERVALS FOR CAT. C6-C10

1	0.807	0.971	0.642	0.921	0.586	0.876	0.771	0.942	0.611	0.962
2	0.872	0.988	0.752	0.966	0.881	0.997	0.789	0.950	0.657	0.973
3	0.675	0.966	0.665	0.946	0.710	0.967	0.804	0.965	0.644	0.979
4	0.844	0.996	0.747	0.979	0.821	0.991	0.808	0.966	0.736	0.997
5	0.840	0.987	0.727	0.971	0.545	0.857	0.793	0.958	0.644	0.979
6	0.827	0.996	0.835	0.997	0.791	0.985	0.819	0.971	0.749	0.997
7	0.877	0.997	0.759	0.984	0.755	0.982	0.825	0.970	0.611	0.962
8	0.385	0.704	0.465	0.812	0.616	0.880	0.759	0.944	0.549	0.940
9	0.746	0.954	0.615	0.914	0.783	0.963	0.797	0.961	0.749	0.997
10	0.723	0.924	0.588	0.892	0.736	0.957	0.789	0.952	0.743	0.997
11	0.733	1.000	0.765	0.999	0.737	1.000	0.811	0.970	0.662	0.987
12	0.451	0.950	0.406	0.843	0.470	0.945	0.788	0.960	0.586	0.968
13	0.671	1.000	0.523	0.986	0.801	1.000	0.794	0.966	0.640	0.993
14	0.744	0.974	0.700	0.957	0.746	0.967	0.805	0.965	0.594	0.952
15	0.856	1.000	0.747	0.994	0.775	0.993	0.811	0.970	0.580	0.951
16	0.894	1.000	0.796	0.987	0.763	0.974	0.819	0.971	0.604	0.961
17	0.895	1.000	0.823	0.999	0.856	1.000	0.808	0.966	0.714	0.996
18	0.876	0.999	0.850	0.997	0.869	0.996	0.826	0.973	0.658	0.980
19	0.812	0.978	0.701	0.944	0.737	0.937	0.809	0.966	0.743	0.997
20	0.654	0.934	0.532	0.863	0.689	0.944	0.797	0.961	0.705	0.989
21	0.464	0.928	0.463	0.863	0.323	0.797	0.792	0.961	0.549	0.940
22	0.815	0.982	0.670	0.947	0.837	0.989	0.829	0.974	0.717	0.990
23	0.909	1.000	0.789	0.983	0.862	0.993	0.804	0.963	0.691	0.989
24	0.851	0.999	0.758	0.980	0.688	0.954	0.793	0.961	0.698	0.989
25	0.733	0.968	0.704	0.958	0.653	0.937	0.804	0.965	0.672	0.981
26	0.704	0.964	0.617	0.943	0.617	0.923	0.814	0.970	0.684	0.988
27	0.933	1.000	0.847	0.994	0.924	0.999	0.810	0.964	0.711	0.990

The empirical estimates for $\bar{\eta}_j$ and D_j applied here are:

$$\hat{\eta}_{j,N} = \frac{1}{N} \sum_{i=1}^{N} Y_{ij} \quad , \tag{4.3}$$

and

$$\hat{D}_{j,N} = \left[\frac{1}{N} \sum_{i=1}^{N} Y_{ij}^2 - \hat{\eta}_{j,N}^2 - H_{j,N}^{-1} \right]^+ \quad , \tag{4.4}$$

where $[a]^+ = \max(a,0)$, and $H_{j,N}$ is the harmonic mean of M_{ij} , i.e., $H_{j,N}^{-1} = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{M_{ij}}$. Notice that $\hat{\eta}_{j,N}$ is a strongly consistent estimator of $\bar{\eta}_j$ (approaches $\bar{\eta}_j$ a.s. as $N \to \infty$) . Assuming that $H_{j,N}$ converges to a limit as $N \to \infty$, $\hat{D}_{j,N}$ converges to D_j as N grows. The values of $\hat{\eta}_{j,N}$ and $D_{j,N}$ obtained in this manner are given in Table 4.2.

Table 4.2
Empirical Estimates
of $\bar{\eta}_j$ and D_j

j	$\bar{\eta}_{j,N}$	$\hat{D}_{j,N}$
1	2.5851	0.0755
2	2.4125	0.1058
3	2.4494	0.0297
4	2.1691	0.1464
5	2.5379	0.0871
6	2.5185	0.0994
7	2.3468	0.0751
8	2.4176	0.0917
9	2.4886	0.0086
10	2.3883	0.0388

5. Estimating the Correlations

The marginal bivariate predictive distribution of Y_{ij} and $Y_{ij'}$, for $j \neq j'$ is normal with p.d.f.

$$f(Y_{ij}, Y_{ij'}; \bar{\eta}_j, \bar{\eta}_{j'}, \rho_{jj'}, D_j, D_{j'}) =$$

$$\frac{1}{2\pi} \cdot \left(\frac{M_{ij}}{1 + D_j M_{ij}}\right)^{1/2} \left(\frac{M_{ij'}}{1 + D_j M_{ij'}}\right)^{1/2} \cdot \frac{1}{\sqrt{1-\rho^2_{jj'}}} \cdot$$

$$\exp\left\{- \frac{1}{2(1-\rho^2_{jj'})} \left[\frac{M_{ij}}{1 + M_{ij} D_j} \left(Y_{ij} - \bar{\eta}_j\right)^2 + \frac{M_{ij'}}{1 + M_{ij} D_{j'}} \left(Y_{ij'} - \eta_{j'}\right)^2 \right.\right.$$
$$\left.\left. - 2\rho_{jj'} \frac{\left(Y_{ij} - \bar{\eta}_j\right)\sqrt{M_{ij}}}{\sqrt{1 + M_{ij} D_j}} \cdot \frac{\left(Y_{ij'} - \bar{\eta}_{j'}\right)\sqrt{M_{ij'}}}{\sqrt{1 + M_{ij} D_j}} \right]\right\} \tag{5.1}$$

Define the weight functions

$$W_{ij} = \frac{M_{ij}}{1 + M_{ij} D_j}, \quad i=1,\ldots,N, \; j=1,\ldots,K. \tag{5.2}$$

If the prior means and variances, $\bar{\eta}_j$, D_j $(j=1,\ldots,k)$ are known, then, the predictive quasi-likelihood function of $\rho_{jj'}$, given the sample data is

$$L(\rho_{jj'} | Y_{ij}, Y_{ij}, i=1,\ldots,N) =$$

$$\left(1-\rho^2_{jj'}\right)^{-N/2} \exp\left\{- \frac{1}{2(1-\rho^2_{jj'})} \left[\sum_{i=1}^{N} W_{ij}(Y_{ij} - \bar{\eta}_j)^2 + \right.\right.$$
$$\left.\left. \sum_{i=1}^{N} W_{ij}(Y_{ij'} - \bar{\eta}_{j'})^2 - 2\rho_{jj'} \sum_{i=1}^{N} \sqrt{W_{ij} W_{ij'}} \left(Y_{ij} - \bar{\eta}_j\right)\left(Y_{ij'} - \bar{\eta}_{j'}\right)\right]\right\} \tag{5.3}$$

(5.3) is called a 'quasi-likelihood' since the correct likelihood function is based on the k-variate distributions of $\underset{\sim}{Y}_1, \ldots, \underset{\sim}{Y}_N$.

In practice, $\bar{\eta}_j$ and D_j are unknown, we will therefore use the quasi-likelihood function of $\rho_{jj'}$ by substituting in (5.3) estimates of $\bar{\eta}_j$ and D_j. Thus, let

$$S_j^2 = \sum_{i=1}^{N} \hat{W}_{ij}(Y_{ij} - \hat{\eta}_j)^2 \qquad , j=1,\ldots,k$$

and (5.4)

$$P_{jj'} = \sum_{i=1}^{N} \sqrt{\hat{W}_{ij}\hat{W}_{ij'}}\,(Y_{ij} - \hat{\eta}_j)(Y_{ij'} - \hat{\eta}_{j'}) \quad , j \neq j'$$

where

$$\hat{\eta}_j = \sum_{i=1}^{N} \hat{W}_{ij}Y_{ij} \Big/ \sum_{i=1}^{N} \hat{W}_{ij} \quad , \tag{5.5}$$

and

$$\hat{W}_{ij} = M_{ij}/(1 + M_{ij}\hat{D}_{j,N}) \quad . \tag{5.6}$$

The estimator $\hat{\rho}_{j,j'}$, which maximizes the log-quasi-likelihood

$$\ell(\rho_{jj'}) = \frac{N}{2}\log(1-\rho_{jj'}^2) - \frac{1}{2(1-\rho_{jj'}^2)}\left[S_j^2 + S_{j'}^2 - 2\rho_{jj'}P_{jj'}\right] \quad , \tag{5.7}$$

is called quasi-maximum likelihood (q.m.l.) estimator of $\rho_{jj'}$. The derivative of $\ell(\rho)$ with respect to ρ is

$$\frac{\partial \ell(\rho)}{\partial \rho} = N\frac{\rho}{1-\rho^2} - \frac{\rho(S_j^2 + S_{j'}^2) - P_{jj'}(1+\rho^2)}{(1-\rho^2)^2} \quad . \tag{5.8}$$

Accordingly, the q.m.l. estimator of $\rho_{jj'}$ is a solution of the cubic equation

$$\rho^3 - \frac{P_{jj'}}{N}\rho^2 + \left(\frac{S_j^2}{n} + \frac{S_{j'}^2}{n} - 1\right)\rho - \frac{P_{jj'}}{n} = 0 \qquad (5.9)$$

for which the second derivative of (5.7) is negative. Accordingly, for given values of $\hat{D}_{j,N}$ $(j=1,\ldots,k)$, we determine $\hat{W}_{ij}$ $(i=1,\ldots,N_j$ $j=1,\ldots,k)$, and $\hat{\eta}_j$ $(j=1,\ldots,k)$ and solve (5.9) by the Newton-Raphson method, starting with the initial solutions

$$\tilde{\rho}_j = 2P_{jj'}/(S_j^2 + S_{j'}^2) \quad , \quad j=1,\ldots,k \qquad (5.10)$$

In Table 5.1 we provide the initial estimates of the correlations (5.10) and the final estimates, which are the solutions of (5.9). The estimates of D_j are those given in Table 4.2. Two numbers are given in each cell of the matrix of final estimates of the correlations. The upper number is the correlation and the lower number is an estimate of its standard error, namely

$$\text{S.E. } \{\hat{\rho}_{jj'}\} = (1-\hat{\rho}_{jj'}^2)/\sqrt{N(1 + \hat{\rho}_{jj'}^2)} \quad . \qquad (5.11)$$

Every estimate $\hat{\rho}_{jj'}$, which, in absolute value, is greater than 2 S.E.$\{\hat{\rho}_{jj'}\}$ is significant.

Table 5.1

Initial and final estimates of the correlation parameters

INITIAL ESTIMATES OF CORRELATIONS

1.000	0.765	0.168	0.360	0.373	0.678	0.593	0.692	0.616	0.406
0.765	1.000	0.029	0.442	0.444	0.851	0.781	0.763	0.635	0.593
0.168	0.029	1.000	0.321	0.321	0.183	0.122	0.099	-0.133	0.140
0.360	0.442	0.321	1.000	0.385	0.341	0.336	0.381	0.305	0.565
0.373	0.444	0.321	0.385	1.000	0.613	0.560	0.542	0.364	0.354
0.678	0.851	0.183	0.341	0.613	1.000	0.924	0.721	0.623	0.386
0.593	0.781	0.122	0.336	0.560	0.924	1.000	0.719	0.641	0.333
0.692	0.763	0.099	0.381	0.542	0.721	0.719	1.000	0.491	0.489
0.616	0.635	-0.133	0.305	0.364	0.623	0.641	0.491	1.000	0.322
0.406	0.593	0.140	0.565	0.354	0.386	0.333	0.489	0.322	1.000

FINAL ESTIMATES OF CORRELATIONS

1	1.000	0.760	0.163	0.355	0.348	0.676	0.587	0.694	0.583	0.394
	0.0	0.065	0.185	0.158	0.160	0.087	0.109	0.082	0.110	0.151
2	0.760	1.000	0.029	0.443	0.421	0.853	0.781	0.769	0.607	0.587
	0.065	0.0	0.192	0.141	0.146	0.040	0.059	0.062	0.104	0.109
3	0.163	0.029	1.000	0.319	0.299	0.183	0.120	0.101	-0.120	0.136
	0.185	0.192	0.0	0.165	0.168	0.183	0.188	0.190	0.188	0.187
4	0.355	0.443	0.319	1.000	0.366	0.347	0.339	0.392	0.283	0.561
	0.158	0.141	0.165	0.0	0.157	0.160	0.161	0.152	0.170	0.115
5	0.348	0.421	0.299	0.366	1.000	0.596	0.538	0.527	0.322	0.330
	0.160	0.146	0.168	0.157	0.0	0.107	0.120	0.123	0.164	0.163
6	0.676	0.853	0.183	0.347	0.596	1.000	0.926	0.732	0.599	0.385
	0.087	0.040	0.183	0.160	0.107	0.0	0.020	0.072	0.106	0.153
7	0.587	0.781	0.120	0.339	0.538	0.926	1.000	0.726	0.615	0.328
	0.109	0.059	0.188	0.161	0.120	0.020	0.0	0.074	0.102	0.163
8	0.694	0.769	0.101	0.392	0.527	0.732	0.726	1.000	0.469	0.492
	0.082	0.062	0.190	0.152	0.123	0.072	0.074	0.0	0.136	0.131
9	0.583	0.607	-0.120	0.283	0.322	0.599	0.615	0.469	1.000	0.294
	0.110	0.104	0.188	0.170	0.164	0.106	0.102	0.136	0.0	0.169
10	0.394	0.587	0.136	0.561	0.330	0.385	0.328	0.492	0.294	1.000
	0.151	0.109	0.187	0.115	0.163	0.153	0.163	0.131	0.169	0.0

6. Summary

In the current paper we present confidence intervals for the category scores as well as the correlations between the scores. The category scores help determine the weaknesses and the strengths of the units. It is important to obtain confidence intervals on these scores because before planning remedial training it is necessary to know whether or not the scores are meaningful. Thus high correlation between two categories may indicate that training to improve the performance in one can improve the performance in the other.

The results in Table 5.1 are intuitively explainable. We obtain high correlation between the categories evaluating the command's performance - Categories 1, 2, 6, 7, and 8. But Categories 3 (Communicating), 4 (Performing as Marines), 5 (Delivering supporting fire) and 10 (Supervising required actions of individual Marines) evaluate the performance of various specific groups and thus each of them cannot be expected to have high correlation with other categories.

A major finding - see Appendix A - is that, for any one battalion, the probability of "Yes" for a given requirement is the same for applicable requirements of the same category. This provides considerable justification for the use of 10 category scores as a measure of the overall capability of the battalion.

APPENDIX 1

We consider here the question of testing assumption A.2.

Typically, for a given evaluation, there are a certain number of "Yes's" among the applicable requirements. The question is how to test the hypothesis that the probability of a "Yes" in a given evaluation depends only on the category to which the requirement belongs. We have tested whether this hypothesis is supported by the data, in the following manner.

The data sets corresponding to the N = 27 different evaluations are arranged according to tasks within 17 different Military Performance Standards (MPS; see [7]). We therefore considered first the number of "Yes's" among the applicable requirements within each cell of MPS x category, for each evaluation. In Table A.1 we present these statistics, as an example, for EVAL 1. An exact test of the hypothesis that the probability of "Yes" is the same for all the MPS's within a category would be very difficult to perform, due to the small number of applicable requirements in each cell.

Let θ_{ikj} denote the probability of "Yes" in EVAL i, MPS k, Category j $(i=1,\ldots,27\ ;\ k=1,\ldots 17\ ;\ j=1,\ldots,10)$. We consider the set of null hypotheses:

$$H_0^{(i,j)}: \theta_{ikj} = \theta_{ij} \quad \underline{\text{for all}} \quad k=1,\ldots,17\ ;$$

$$\text{at each} \quad i=1,\ldots,27\ ;\ j=1,\ldots,10\ .$$

In the spirit of the Bayesian approach of Section 3, we assume, a priori, that θ_{ikj} are independent random variables, having some prior distributions

$H_{kj}(\theta)$ $(k=1,\ldots,17\ ;\ j=1,\ldots,10)$. If the null hypotheses $H_0^{(i,j)}$ are true for all (i,j), the following null hypotheses should also be true: For each j, $j=1,\ldots,10$,

$$H_0^{(\cdot,j)}: \quad \Psi_{kj} = \Psi_j \quad \underline{\text{for all}} \quad k=1,\ldots,17\ ,$$

where

$$\Psi_{kj} = \int_0^1 \theta_{ijk} dH_{kj}(\theta_{ijk}) \tag{A.1.1}$$

Table A.1

The number of satisfied (upper) and applicable (lower) requirement by MPS and Category for Eval. 1

MPS	CATEGORIES 1	2	3	4	5	6	7	8	9	10
2.A.1	9	4	4	11	0	3	14	4	2	6
	11	9	4	19	0	3	18	13	3	10
2.A.2	8	0	20	0	7	10	15	9	9	3
	9	0	20	1	8	10	18	9	9	3
2.A.3	0	0	2	0	35	3	0	0	0	0
	0	0	2	0	48	5	1	0	0	0
2.B.1	6	0	0	0	0	5	2	5	0	2
	6	0	0	0	0	5	3	5	1	2
2.B.2	7	5	1	2	0	8	3	7	2	1
	7	6	1	2	0	9	3	10	2	1
2.B.3	8	5	3	0	1	2	1	11	0	0
	8	5	3	0	1	3	1	14	0	0
2.B.4	9	3	1	0	2	9	5	12	2	1
	10	5	1	0	2	11	8	13	2	1
2.B.5	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0
2.B.6	2	3	2	1	2	10	2	0	0	0
	2	4	2	1	2	12	3	0	0	0
2.B.7	3	2	0	0	0	6	0	1	2	0
	4	2	0	0	0	7	0	2	3	0
2.C.1	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0
2.C.2	3	3	1	0	0	4	1	1	0	0
	3	3	1	0	0	4	1	4	0	0
2.C.3	0	0	0	0	0	0	0	0	0	0
	0	0	0	0	0	0	0	0	0	0
2.C.4	3	2	0	0	0	3	4	0	0	0
	3	2	0	0	0	3	4	0	0	0
2.D.1	2	3	6	0	8	34	0	0	4	0
	2	3	6	0	8	34	0	0	4	0
2.D.2	2	6	0	0	0	2	3	3	3	0
	2	6	0	0	0	2	3	3	8	0
2.D.3	0	8	0	0	0	1	0	0	0	0
	0	9	0	0	0	2	0	0	0	0
VOL. II	62	44	40	14	55	100	50	53	24	13
	67	54	40	23	69	110	63	73	32	17

Let Ψ^*_{kj} and M^*_{kj} $(k=1,\ldots,17\ ,\ j=1,\ldots,10)$ be the number of satisfied and applicable requirements in the k-th MPS and j-th category, summed over all the 27 evaluations. Let

$$X^*_{\cdot j} = \sum_{k=1}^{17} X^*_{kj}$$

$$(j=1,\ldots,10) \qquad \text{(A.1.2)}$$

and

$$M^*_{\cdot j} = \sum_{k=1}^{17} M^*_{kj}$$

These statistics are given in Table A.2. We see in Table A.2 that the values of $M^*_{\cdot j}$ are large ones, for all $j=1,\ldots,k$; and that M^*_{kj} are generally not too small. We therefore consider, for each hypothesis $H_0^{(\cdot,j)}$, the chi-squared statistic

$$T_j^2 = \sum_{k=1}^{k^*_j} \frac{(X^*_{kj} - E^*_{kj})^2}{E^*_{kj}} I^*_{kj} \quad , \qquad \text{(A.1.3)}$$

where

$$E^*_{kj} = M^*_{kj} \frac{X^*_{\cdot j}}{M^*_{\cdot j}} \quad , \quad \begin{matrix} k=1,\ldots,17 \\ j=1,\ldots,10 \end{matrix} \qquad \text{(A.1.4)}$$

$$I^*_{kj} = \begin{cases} 1 \ , & \text{if } M^*_{kj} > 0 \\ 0 \ , & \text{if } M^*_{kj} = 0 \end{cases} \qquad \text{(A.1.5)}$$

and $k^*_j = \sum_{k=1}^{17} I_{kj}$. The estimates of the expected values of X^*_{kj} , under the null hypothesis $H_0^{(\cdot,j)}$, are E^*_{kj} . The large sample distribution of T_j^2 is like that of a chi-squared random variable with $\nu_j = k^*_j - 1$ degrees of freedom. In Table A.3 we provide the values of T_j^2 and their P - values

$$P_j = P\ \{X^2[\nu_j] \geq T_j^2 | T_j^2\} \ , \quad j=1,\ldots,10 \qquad \text{(A.1.6)}$$

Table A.2

The statistics $X^{*}_{\cdot j}$ and $M^{*}_{\cdot j}$

1	214	158	66	366	0	65	351	216	64	219
1	245	199	93	472	0	70	413	283	75	258
2	212	0	416	18	162	218	367	204	207	70
2	232	0	447	26	182	239	440	228	225	75
3	0	0	36	0	993	77	21	0	0	0
3	0	0	49	0	1121	106	24	0	0	0
4	63	0	0	7	13	48	24	74	24	18
4	63	0	0	9	13	49	27	77	27	18
5	110	99	11	33	24	142	51	162	20	26
5	121	110	15	37	25	164	54	189	22	34
6	101	64	39	0	10	32	9	180	0	0
6	113	74	40	0	10	37	10	193	0	0
7	225	123	22	0	36	260	178	347	43	20
7	243	140	22	0	40	282	211	372	43	21
8	48	54	30	22	0	97	62	70	7	0
8	53	68	31	26	0	105	72	89	8	0
9	118	89	40	38	30	261	96	86	31	0
9	123	101	44	51	33	293	108	94	32	0
10	81	26	0	0	5	132	0	80	32	0
10	83	26	0	0	5	142	0	95	37	0
11	48	31	11	0	2	74	0	104	0	19
11	48	33	12	0	2	76	0	107	0	21
12	49	87	19	0	13	75	30	59	0	0
12	54	100	19	0	15	90	36	75	0	0
13	21	17	7	0	9	30	4	41	5	0
13	24	18	7	0	10	36	4	44	6	0
14	28	22	0	0	0	37	26	0	0	0
14	30	23	0	0	0	38	32	0	0	0
15	10	19	29	0	40	178	0	0	20	0
15	10	19	30	0	40	181	0	0	20	0
16	8	24	2	0	0	5	8	12	20	0
16	8	24	2	0	0	5	10	12	28	0
17	0	39	3	0	0	11	0	0	0	0
17	0	43	3	0	0	13	0	0	0	0
TOTAL I	1336	852	731	484	1337	1742	1227	1635	473	372
TOTAL N	1450	978	814	621	1496	1926	1441	1858	523	427

where $X^2[\nu_j]$ is a chi-squared random variable, independent of T_j^2, with ν_j degrees of freedom

Table A.3

The values of T_j^2 and P_j

Cat.	T_j^2	P_j	Cat.	T_j^2	P_j
1	2.155	.99987	6	7.371	.96543
2	3.811	.99304	7	1.200	.99996
3	7.326	.88458	8	10.183	.59991
4	1.089	.95507	9	2.292	.99357
5	1.112	.99991	10	1.452	.91854

We see in Table A.3 that each one of the ten null-hypotheses $H_0^{(\cdot,j)}$ is strongly accepted (very high P - values). Let P^* be the combined P - value of all the ten tests. According to the Bonferroni inequality [4],

$$P^* \geq 1 - \sum_{j=1}^{10} (1-P_j) \quad . \tag{A.1.7}$$

Thus, according to the values in Table A.3, $P^* \geq .30988$. Thus, we simultaneously accept all the ten null hypotheses, with a very high P^* value. Note that, if at least one of the null hypotheses had been rejected we should have concluded that assumption A.2 of Section 2 is not supported by the data. However, since all the null hypotheses have been strongly accepted, we conclude that the data is in accord with assumption A.2.

APPENDIX 2

We show in the present appendix that asymptotically, the correlation between $\hat{\theta}_{ij}$ and $\hat{\theta}_{ij'}$ is equivalent to $\rho_{jj'}$, for $j,j'=1,\ldots,k$.

The inverse of (2.1) is

$$\hat{\theta}_{ij} = \sin^2 (Y_{ij}/2) \quad , \quad \begin{matrix} i=1,\ldots,N \\ j=1,\ldots,k \ . \end{matrix} \tag{A.2.1}$$

where $Y_{ij} \sim N(\eta_{ij}, M_{ij}^{-1})$. Expand $\hat{\theta}_{ij}$ around η_{ij} to obtain

$$\hat{\theta}_{ij} = \sin^2(\eta_{ij}/2) + (Y_{ij} - \eta_{ij}) \sin(\eta_{ij}/2) \cos(\eta_{ij}/2) + 0_P\left(\frac{1}{\sqrt{N}}\right) , \tag{A.2.2}$$

where $0_P(\cdot)$ is an order-of-magnitude-in-probability symbol (see Zacks [5; pp. 208]).

Let $\underset{\sim}{\hat{\theta}}_i = (\hat{\theta}_{i1}, \ldots, \hat{\theta}_{ik})'$ and $\underset{\sim}{\hat{\tau}}_i = \left(\sin^2(\frac{\eta_{i1}}{2}), \ldots, \sin^2(\frac{\eta_{iu}}{2})\right)'$. Notice that $\sin(\frac{\eta}{2}) \cos(\frac{\eta}{2}) = \frac{1}{2} \sin(\eta)$. Let $(D)_i =$ diag $\{\sin(\eta_{i1}), \ldots, \sin(\eta_{ik})\}$.

Then,

$$\underset{\sim}{\hat{\theta}}_i = \underset{\sim}{\tau}_i + \frac{1}{2} (D)_i (\underset{\sim}{Y}_i - \underset{\sim}{\eta}_i) + 0_P(\frac{1}{\sqrt{N}}) , \tag{A.2.3}$$

Thus, as $N \to \infty$, the asymptotic covariance matrix of $\underset{\sim}{\hat{\theta}}_i$ is

$$\updownarrow(\underset{\sim}{\hat{\theta}}_i) = \frac{1}{4} (D)_i \updownarrow_i (D)_i , \tag{A.2.4}$$

where the elements of $\updownarrow_i$ are specified in (2.2). Accordingly, the asymptotic variance of $\hat{\theta}_{ij}$ is

$$AV \{\hat{\theta}_{ij}\} = \frac{1}{4} \sin^2(\eta_{ij})/M_{ij} \tag{A.2.5}$$

and the asymptotic covariance of $\hat{\theta}_{ij}$ and $\hat{\theta}_{ij'}$, $j \neq j'$, is

$$AC(\hat{\theta}_{ij}, \hat{\theta}_{ij'}) = \frac{1}{4} \rho_{jj'} \sin(\eta_{ij}) \sin(\eta_{ij'}) / \sqrt{M_{ij} M_{ij'}} \tag{A.2.6}$$

Hence, the asymptotic correlation between $\hat{\theta}_{ij}$ and $\hat{\theta}_{ij'}$ is $\rho_{jj'}$, for all $i=1,\ldots,N$.

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